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Review

Advances in Coronary Computed Tomography Angiography: From Plaque Characterization to Prognostic Assessment and Clinical Decision-Making

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Abstract

The increasing incidence and persistently high mortality of coronary artery disease (CAD), the leading cardiovascular disease worldwide, necessitate improved approaches to prognostic assessment and clinical decision-making. Coronary stenosis has long guided CAD-related risk stratification and treatment; however, plaque characteristics exhibit a stronger association with major adverse cardiovascular events. Consequently, coronary computed tomography angiography (CCTA) has evolved from a technique primarily used to assess luminal stenosis into a comprehensive imaging modality for plaque characterization, functional evaluation, prognostic assessment, and clinical decision-making. Herein, we systematically summarize recent advances in photon-counting detector computed tomography (CT), the use of large language models for CCTA reporting, and artificial intelligence applications in CCTA; discuss the implications of these developments for prognostic assessment and clinical decision-making; address the current limitations and challenges for clinical implementation. Further technical refinement and prospective validation are expected to expand the role of CCTA in risk stratification and individualized management of CAD.

Keywords: coronary computed tomography angiography; artificial intelligence; coronary artery disease; plaque characterization; prognostic assessment; clinical decision-making

1. Introduction

Coronary artery disease (CAD) is the leading cause of mortality worldwide [1]. Although coronary stenosis has long been considered the main determinant of cardiovascular risk stratification and treatment decisions, mounting evidence suggests that plaque characteristics are better predictors of major adverse cardiovascular events (MACEs) than stenosis alone [2], which highlights the need for comprehensive plaque characterization beyond luminal stenosis.

Coronary computed tomography angiography (CCTA) is an established noninvasive modality for evaluating suspected CAD, with current guidelines recommending CCTA for ruling out obstructive CAD and detecting nonobstructive atherosclerotic disease [3]. Technological innovations have substantially expanded the role of CCTA, which evolved from a technique used primarily to assess luminal stenosis into a high-spatial-resolution multidimensional imaging modality enabling anatomical and functional plaque characterization [4] and the identification of high-risk plaque characteristics. The integration of CT-derived fractional flow reserve (CT-FFR) has extended assessment to functional significance, while advances in artificial intelligence (AI) have enabled more precise and reproducible plaque quantification [5,6]. Thus, improved plaque characterization has rendered CCTA better suited for prognostic assessment and clinical decision-making.

This review summarizes the latest advances in CCTA use for coronary plaque characterization and their clinical implications (Fig. 1). The related original research articles, clinical trials, and reviews published up to April 30, 2026 were identified by searching PubMed and the Web of Science using "coronary CT angiography", "photon-counting detector CT", "large language models", "artificial intelligence", "plaque", and "coronary artery disease" along with their synonyms and related terms as search terms, and selected based on scientific quality and relevance. After summarizing recent technological advances in CCTA (Fig. 2), we discuss their beneficial effects on the assessment of plaque characterization (Table 1) [7,8,9,10,11,12,13,14,15,16,17], implications for prognostic assessment across diverse patient populations, and nascent role in guiding clinical decision-making. These advances highlight a paradigm shift in CAD assessment from luminal stenosis to plaque characterization and have important implications for precise risk stratification and individualized treatment.

2. Advent of Photon-Counting Detector CT (PCD-CT)

Although conventional energy-integrating detector CT (EID-CT) plays an important role in CAD management, its use is constrained by limited spatial resolution, radiation exposure, and susceptibility to artifacts such as

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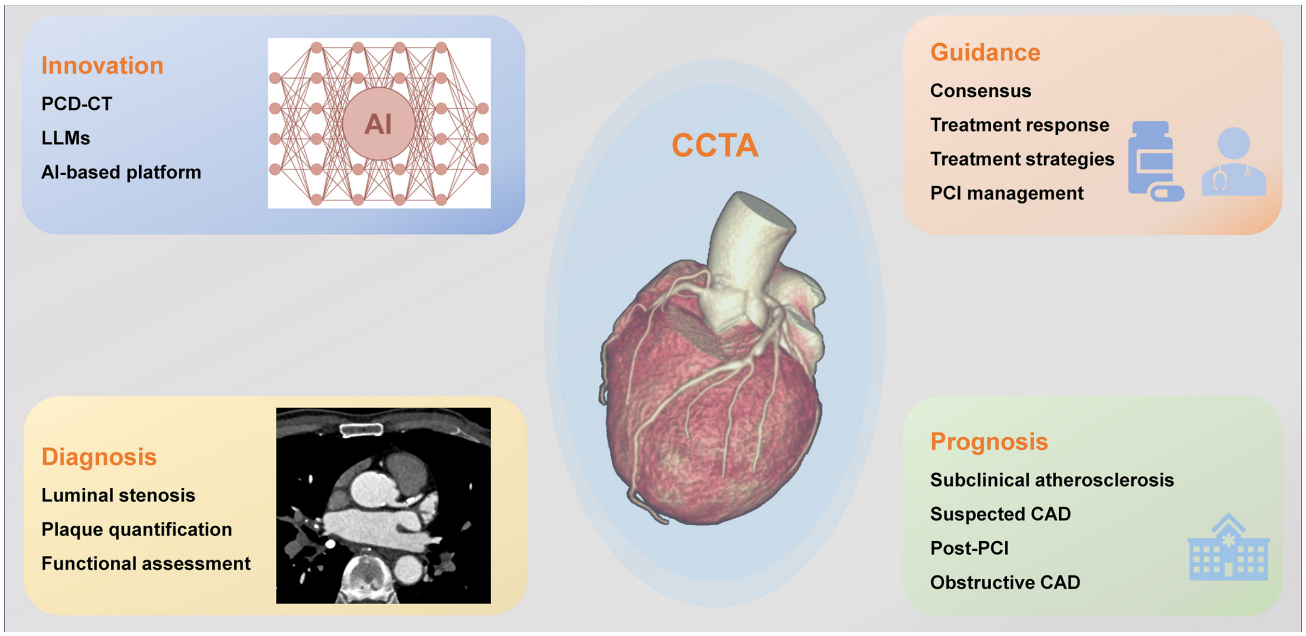


Fig. 1. Schematic of recent advances in CCTA, including technological innovations, plaque characterization, prognostic assessment, and clinical decision-making. AI, artificial intelligence; CAD, coronary artery disease; CCTA, coronary computed tomography angiography; LLM, large language model; PCD-CT, photon-counting detector computed tomography; PCI, percutaneous coronary intervention.

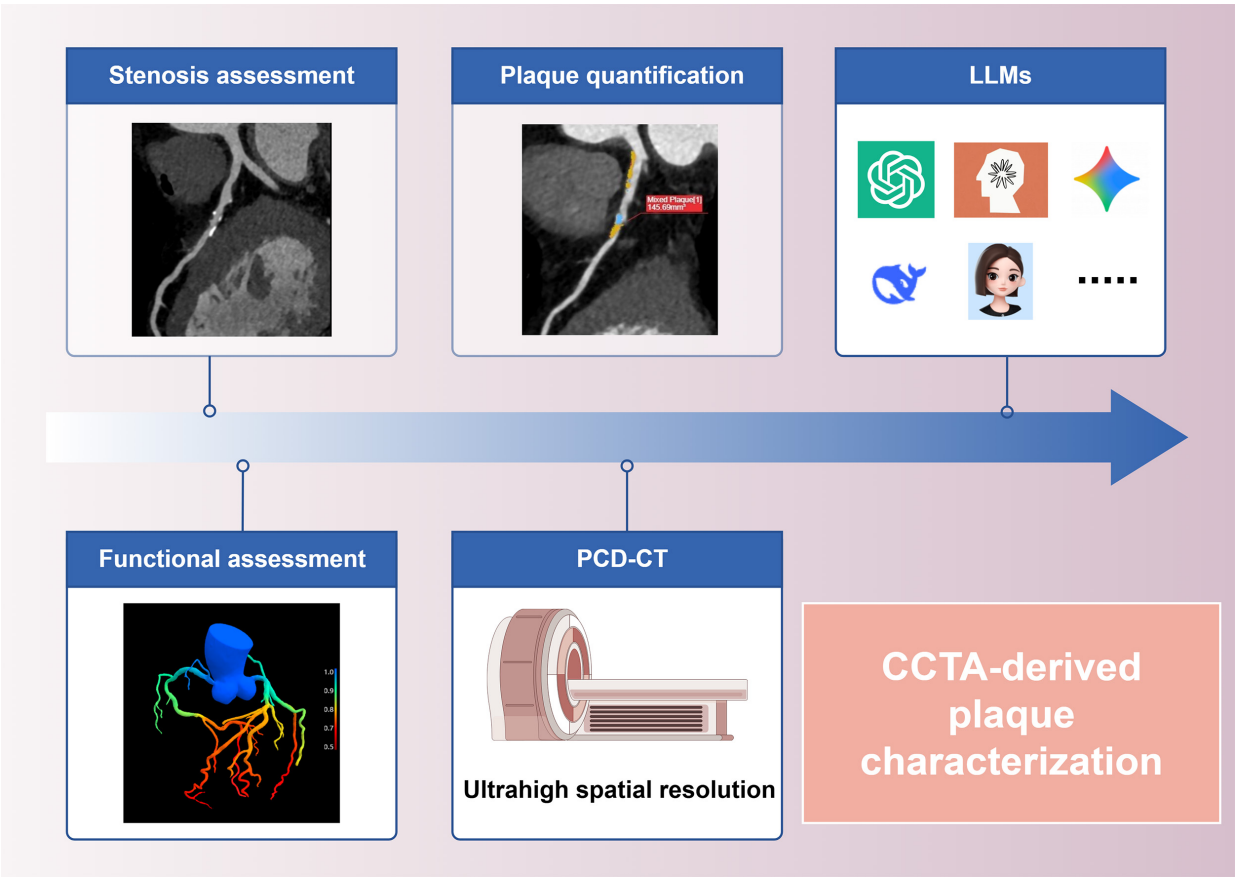


Fig. 2. Development of CCTA-derived plaque characterization. CCTA, coronary computed tomography angiography; LLM, large language model; PCD-CT, photon-counting detector computed tomography.

Table 1. Overview of the latest advances in CCTA.

Study	Technique	Clinical issue	Sample size	Main findings
Parikh et al. [7]	PCD-CT	Luminal stenosis	1571	Improved diagnostic accuracy and fewer indeterminate findings compared with EID-CT
Demmert et al. [8]	PCD-CT	Luminal stenosis	62	High diagnostic accuracy and strong agreement with ICA
Hagar et al. [9]	PCD-CT	Coronary stent patency	44	High image quality, high diagnostic accuracy, and strong agreement with ICA
Vecsey-Nagy et al. [10]	PCD-CT	Plaque quantification	164	Lower total plaque volume, lower fibrotic plaque volumes, and higher low-attenuation plaque volumes compared with EID-CT
Sun et al. [11]	PCD-CT	Plaque quantification	4	More precise delineation of plaque boundaries, necrotic core extent, fibrous plaque, and intraplaque hemorrhage with *ex vivo* hearts as the reference standard
Yoo et al. [12]	LLMs	CAD-RADS 2.0 categories and modifiers	507	o1 model achieved the highest accuracy
Min et al. [13]	LLMs	CAD-RADS 2.0 categories and modifiers	319	GPT-4o and o1-mini showing particularly high accuracy
Kay et al. [14]	AI	Luminal stenosis and plaque quantification	1041	Near-perfect agreement with expert readers
Bernardo et al. [15]	AI	Luminal stenosis and plaque quantification	208	Better agreement with invasive QCA than radiologists
Han et al. [16]	AI	Empower radiologists	200	Improved diagnostic performance and reduced interpretation time
Fazzari et al. [17]	AI	On-site CT-FFR	250	Diagnostic accuracy and agreement comparable to HeartFlow CT-FFR

AI, artificial intelligence; CAD-RADS, Coronary Artery Disease Reporting and Data System; CCTA, coronary computed tomography angiography; CT-FFR, CT-derived fractional flow reserve; EID-CT, energy-integrating detector CT; ICA, invasive coronary angiography; LLMs, large language models; PCD-CT, photon-counting detector CT; QCA, quantitative coronary angiography.

blooming and beam hardening [18]. PCD-CT represents a major technological advance over EID-CT, relying on the direct conversion of X-ray photons to electrical signals to eliminate the intermediate light conversion step required by EID-CT and thereby enhancing spatial resolution and image quality while enabling simultaneous multi-energy spectral sampling [7,18]. These technical advantages facilitate the assessment of coronary stenosis and accurate plaque quantification. In addition, PCD-CT is well suited for complex clinical scenarios; e.g., in patients with difficult venous access, it facilitates ultralow-flow contrast injection while preserving an image quality comparable with that of standard protocols [19]. Compared with EID-CT (**Supplementary Tables 1,2**), PCD-CT reduces radiation exposure without compromising diagnostic accuracy [20,21] and may therefore support safer imaging strategies, particularly in patients requiring serial assessments.

2.1 PCD-CT Facilitates Luminal Stenosis and Stent Patency Assessment

Heavily calcified lesions and coronary stents remain major challenges for conventional EID-CT, as blooming artifacts frequently result in luminal stenosis and stent patency overestimation. PCD-CT can mitigate the impact of artifacts on stenosis assessment by combining ultrahigh spatial resolution (up to 0.2 mm) with intrinsic spectral imaging capability. In a retrospective study [7] of 1571 elderly patients comparing EID-CT with PCD-CT, the latter achieved a markedly lower diagnostic uncertainty (8.8% vs. 14.6%) and higher diagnostic accuracy (95.5% vs. 90.3%) in patients with severe coronary calcification. Demmert et al. [8] reported good interreader agreement (Cohen's kappa = 0.71–1.00) for stenosis diagnosis using PCD-CT in patients with coronary artery calcium scores (CACS) of >600 and demonstrated that high sensitivity and specificity were preserved even at scores of >3000. Moreover, PCD-CT outperformed EID-CT in terms of diagnostic performance in the evaluation of in-stent restenosis after coronary stent implantation while maintaining good concordance with invasive coronary angiography (ICA) [9,22]. Although PCD-CT shows clear advantages in reducing blooming artifacts, it does not markedly outperform EID-CT in mitigating motion artifacts or noise, which highlights the need for further refinement of reconstruction algorithms. Moreover, given that the transition from EID-CT to PCD-CT involves changes in image characteristics, an adaptation period may be required for radiologists. Further research is needed to standardize the widespread clinical implementation of PCD-CT.

2.2 PCD-CT Facilitates Plaque Quantification

Blooming artifacts and limited spatial resolution limit the plaque quantification performance of EID-CT, leading to the overestimation of calcified plaque and reduced accuracy in the measurement of noncalcified plaque [10]. Therefore, much attention has been paid to the value of PCD-CT in quantitative plaque analysis. In an intraindividual comparative study of 164 plaques from 48 patients [10], PCD-CT outperformed EID-CT in terms of the accuracy of quantitative plaque assessment, yielding lower plaque volumes that better reflect the true atherosclerotic burden (723.5 mm^3 [Interquartile range (IQR), 500.6–1184.7 mm^3] vs. 1084.7 mm^3 [IQR, 710.7–1609.8 mm^3]; $p < 0.001$). PCD-CT also enabled the highly reproducible characterization of fibrous and low-attenuation plaques, thus increasing the robustness of plaque quantification. In an *ex vivo* heart study [11], PCD-CT enabled a more precise delineation of plaque boundaries, necrotic core extent, fibrous plaque, calcified plaque, and intraplaque hemorrhage than EID-CT. These findings provide pathology-correlated evidence of PCD-CT improving the accuracy and reproducibility of plaque quantification. The direct comparison of EID-CT and PCD-CT in terms of plaque quantification performance in larger cohorts is challenging because of radiation exposure concerns, which may limit the generalizability of the findings.

3. Applications of Large Language Models (LLMs) in CCTA Reporting

The rise of LLMs holds promise for the realization of more standardized and reproducible CCTA reporting, with attendant benefits including reduced documentation demands and enhanced diagnostic clarity [23,24]. Although Coronary Artery Disease Reporting and Data System (CAD-RADS) 2.0 provides a standardized framework for CCTA reporting [25], its clinical implementation remains limited by increased time demands and variability in reporting. These inconsistencies may lead to the misclassification of stenosis severity and underdetection of high-risk plaque features [26], underscoring the need for reliable automated support. LLMs may help address this need by improving the standardization and consistency of CCTA reporting, reducing workload, and enhancing diagnostic clarity. Yoo et al. [12] compared four LLMs with four human readers of varying experience for CAD-RADS 2.0 classification, revealing that OpenAI o1 achieved the highest accuracy and all LLMs featured report processing times markedly shorter than those of human readers (1.34–16.61 s vs. 32.10–55.06 s). Min et al. [13] demonstrated that six LLMs could accurately extract the core CAD-RADS 2.0 elements from reports, with GPT-4o and OpenAI o1-mini showing particularly high accuracy for stenosis severity and plaque burden assessment in external testing. Modifier detection accuracy remained consistently high (≥0.99) in most models. These findings support the feasibility of using LLMs as practical tools for improving the quality of CCTA reporting. Future prospective multicenter studies are warranted to determine the real-world impact of LLMs on clinical decision-making and patient outcomes.

4. AI-Enabled CCTA for CAD Assessment

Recent advances in AI, particularly in reconstruction and diagnostic algorithms, have enhanced the diagnostic performance of CCTA [27,28], with AI-based platforms currently achieving rapid automated coronary artery segmentation and diagnostic assessment within minutes [6,29]. As a result, CCTA has achieved notable progress in coronary stenosis evaluation, plaque quantification, and functional assessment.

4.1 AI-Enabled Assessment of Luminal Stenosis

Although the diagnostic performance of AI remains debated [30,31,32], mounting evidence suggests that its accuracy can approach or even exceed that of expert-level interpretation. A retrospective study of 1041 CCTA images [14] demonstrated high agreement between AI and experts in stenosis severity grading. Meta-analytic data and the *post hoc* analyses of the prospective comparison of cardiac PET/CT, SPECT/CT perfusion imaging and CT coronary angiography with invasive coronary angiography (PACIFIC)-1 study revealed that compared with radiologists, AI better detected obstructive coronary stenosis and achieved closer agreement with invasive reference standards, particularly in patients with a high plaque burden [15,33]. In addition, interpretation was found to depend on the radiologist's experience level. AI assistance demonstrated substantial value in improving interreader consistency and diagnostic performance for radiologists while notably reducing interpretation time [16,34]. However, excessive AI assistance may foster overreliance and impair independent diagnostic judgment and AI-related error recognition. Implementing confidence scoring within decision support systems may provide a practical means to enhance human–machine interactions.

4.2 AI-Enabled Plaque Quantification

Plaque quantification using semiautomated software can predict MACEs [6,35] but remains labor-intensive and operator-dependent. The use of AI, especially deep learning algorithms, can increase the efficiency and accuracy of CCTA-derived plaque quantification. Chen et al. [36] developed PlaqueSegNet, a fully automated deep learning model for accurate plaque volume quantification, achieving excellent agreement with the results of expert and intravascular ultrasound measurements (all intraclass correlation coefficients >0.90) and robust consistency and reproducibility across different imaging systems and scanning protocols. Multicenter data from the REVEALPLAQUE study validated the accuracy of AI-enabled plaque quantification and agreed well with the results of intravascular ul-

trasound measurements [37]. Furthermore, AI-determined CACS agreed well with those provided by experts [14]. Despite these advances, the reliability of AI-enabled plaque quantification requires further validation against histology, intravascular ultrasound, or optical coherence tomography, and its reproducibility should be confirmed through repeated scans of the same patient. Regulatory considerations regarding the initial approval and ongoing updates of these algorithms remain an additional challenge. The above findings underscore the promise of AI for enabling accurate, efficient, and standardized plaque quantification in CCTA and highlight areas for further validation and oversight.

4.3 AI-Enabled Functional Assessment

Coronary stenosis severity imperfectly correlates with functional ischemia [38,39]. Against an invasive FFR ≤0.80 reference, stenosis-guided ICA detects ischemia with a sensitivity of 69% and specificity of 67% [40]. However, the invasive nature, high cost, and potential complications of FFR limit its routine clinical use. Owing to progress in computational fluid dynamics and deep learning, CT-FFR can now be extracted from standard CCTA acquisitions, thereby furnishing a noninvasive, safe, and economically efficient approach [5,41,42].

Early CT-FFR algorithms such as HeartFlow have been rigorously validated in multicenter trials, enabling the accurate identification of hemodynamically significant stenosis, reduced downstream ICA utilization, and informed therapeutic decision-making [43,44,45,46]. However, broader clinical adoption is constrained by the reliance on off-site core-laboratory processing [47]. In a comparative study, a deep learning–based on-site CT-FFR algorithm enabled the highly accurate detection of hemodynamically significant stenosis and featured an overall diagnostic performance comparable with that of off-site HeartFlow [17]. Another study demonstrated the high accuracy (91.8%) of on-site CT-FFR for detecting hemodynamically significant coronary stenosis compared with invasive FFR [48]. CT-FFR is particularly valuable in intermediate coronary stenosis, in which case clinical decision-making is often challenging [48,49]. The shorter analysis time of on-site CT-FFR facilitates its integration into routine clinical workflows. This technique is particularly useful in patients presenting with acute chest pain, as it accurately identifies hemodynamically significant stenosis responsible for symptoms [50]. Further studies are warranted to expand the clinical applications of CT-FFR.

5. Applications of CCTA in Prognostic Assessment

Advances in the diagnostic performance of CCTA have substantially increased its role in prognostic assessment. Compared with conventional risk factors, CCTA-derived quantitative plaque features and functional parameters provide more comprehensive and precise prognostic information. Recent large-scale cohort studies have affirmed the independent predictive capacity of CCTA for MACEs, thereby extending its clinical utility from imaging diagnosis to robust cardiovascular risk stratification. The prognostic value of CCTA may be further enhanced via combination with circulating biomarker levels. The recent applications of CCTA in prognostic assessment are presented in Table 2 [51,52,53,54,55,56].

5.1 Risk Assessment in Individuals With Subclinical Coronary Atherosclerosis

Risk assessment in patients with subclinical coronary atherosclerosis is essential for primary prevention. CCTA provides incremental prognostic value beyond traditional risk factors, with markers such as segment involvement score, noncalcified plaque, and obstructive stenosis improving the prediction of first coronary events [51]. In asymptomatic individuals with a family history of premature CAD, the use of CACS is associated with lower atherogenic lipid levels and slower plaque progression when incorporated into preventive strategies [57]. These data indicate that CCTA provides additive prognostic utility in asymptomatic populations, thereby improving the implementation of primary prevention.

5.2 MACEs in Patients With Suspected CAD

AI-guided quantitative CCTA (AI-QCT) enables a more precise and reproducible plaque characterization than manual interpretation. Multiple studies [52,58,59] have shown that AI-QCT has considerable prognostic value for MACEs and provides incremental risk stratification beyond clinical risk factors and CAD-RADS 2.0 in patients with suspected CAD. Moreover, AI-QCT provides incremental prognostic information over CACS in patients with suspected CAD, as demonstrated in a cohort of 2404 patients with a median follow-up of 7.0 years [53]. This fact may be explained by the limitations of CACS, which cannot be used to detect noncalcified plaque or characterize plaque distribution; thus, patients with normal CACS may still be at risk of MACEs due to underlying noncalcified plaque [60]. These findings highlight the prognostic advantage of comprehensive AI-enhanced plaque assessment in patients with suspected CAD.

5.3 Nonculprit Vessel–Related MACEs in Post-Percutaneous Coronary Intervention (PCI) Patients

In patients undergoing PCI, nearly half of MACEs originate from nonculprit vessels, which underscores the clinical importance of identifying high-risk nonculprit lesions [61,62]. In a single-center study involving 2014 nonculprit vessels after PCI, AI was used to automatically extract CCTA features (including substantial stenosis, high-risk plaque, high plaque volume, low CT-FFR, and high pericoronary adipose tissue attenuation) with nonculprit vessel–related MACEs as the primary endpoint. Vessel-specific CT-FFR and necrotic core volume emerged as inde-

Table 2. Applications of CCTA in prognostic assessment.

Study	Clinical issue	Sample size	Applications
Bergström et al. [51]	Individuals with subclinical coronary atherosclerosis	24,791	Improved risk prediction beyond traditional risk factors and CACS in identifying individuals at risk of first coronary events and in need of primary prevention
Van Rosendael et al. [52]	Patients with suspected CAD	1916	AI-QCT had incremental prognostic value for MACEs compared with CAD-RADS 2.0, CACS, and the modified Duke Index
Dahdal et al. [53]	Patients with suspected CAD	2404	AI-QCT enhanced prognostic accuracy for MACEs compared to CACS
Chen et al. [54]	Post-PCI patients	2014	AI-QCT provided independent and incremental prognostic value for nonculprit vessel-related MACEs
Gall et al. [55]	Patients with obstructive CAD	2312	Plaque composition assessment had incremental prognostic value for MACEs compared with traditional risk factors and CAD burden
Dai et al. [56]	Assessment of plaque progression	2588	Using CCTA-assessed plaque progression as a surrogate endpoint

AI-QCT, AI-guided quantitative CCTA; CACS, coronary artery calcium scores; CAD, coronary artery disease; CAD-RADS, Coronary Artery Disease Reporting and Data System; CCTA, coronary computed tomography angiography; MACEs, major adverse cardiovascular events; PCI, percutaneous coronary intervention.

pendent predictors of MACEs, and their incorporation into a clinical risk factor model notably improved its predictive performance [54]. These findings support the independent prognostic value of AI-QCT for nonculprit vessel–related MACEs and suggest its potential role in post-PCI risk stratification. However, further validation in larger multicenter studies is needed.

5.4 MACEs in Patients With Obstructive CAD

In patients with obstructive CAD, risk stratification based solely on stenosis severity has clear limitations [63]. Multiple studies have used CCTA to assess obstructive stenosis and demonstrated its prognostic value for MACEs [64,65]. CCTA-based plaque characterization provides incremental prognostic information. In a multicenter study, CCTA-derived plaque composition analysis, particularly the assessment of noncalcified plaque, markedly improved MACE prediction beyond traditional risk factors [55]. These findings support the prognostic value of CCTA-based plaque characterization in obstructive CAD. Combination with radiomic analysis may further enhance risk stratification. Future studies should clarify how these imaging markers can be integrated into clinical decision-making to optimize individualized management.

5.5 Assessment of Plaque Progression

The serial CCTA-based assessment of plaque progression is increasingly used as a surrogate prognostic endpoint and may help clarify the mechanisms underlying plaque progression. Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) infection has been associated with an increased risk of cardiovascular events [66,67]; however, the underlying mechanisms are incompletely understood. A CCTA-based study [56] showed that patients with SARS-CoV-2 infection experienced a more rapid progression of total and noncalcified plaque burdens, a higher prevalence of high-risk plaque, and increased pericoronary adipose tissue attenuation at follow-up, underscoring the need for closer post-infection plaque surveillance and cardiovascular risk management. Kraaijenhof et al. [68] reported that plasma proteomics enhanced the prediction of CCTA-derived plaque progression and high-risk plaque development. These findings highlight the value of CCTA in capturing dynamic plaque changes and improving risk stratification across diverse clinical settings.

Current evidence supports the robust prognostic value of CCTA across diverse patient populations. The addition of circulating biomarker levels may further improve prognostic assessment. Circulating biomarkers, such as high-sensitivity cardiac troponin T, reflect subclinical myocardial injury, whereas CCTA enables detailed plaque characterization. The integration of these complementary biomarkers may enable more precise risk stratification and support personalized management strategies [69].

6. Applications of CCTA in Clinical Decision-Making

CCTA-determined plaque characteristics have value not only for risk prediction but also for directly informing clinical treatment decisions. Mounting clinical evidence supports the integration of CCTA-determined plaque characteristics into individualized therapeutic pathways. According to the consensus statement from the Quantitative Cardiovascular Imaging study group [70], the presence of any atherosclerotic plaque should prompt the consideration of pharmacological therapy, with treatment intensification recommended for total plaque volumes above the 70th percentile. This framework represents an important

Table 3. Applications of CCTA in clinical decision-making.

Study	Clinical issue	Sample size	Applications
Weichsel et al. [71]	Surveillance of treatment response	216	Moderate- and high-intensity lipid-lowering therapy significantly slowed the progression of total plaque and noncalcified plaque assessed by CCTA
Budoff et al. [72]	Surveillance of treatment response	84	Colchicine more effectively reduced total plaque burden and promoted plaque stabilization assessed by CCTA
Nurmohamed et al. [73]	Treatment strategies	750	AI-QCT support increased physicians' diagnostic confidence, led to changes in 57% of diagnoses or management, reduced downstream testing by 37%, and increased the use of preventive therapies
Yoo et al. [74]	Treatment strategies	21,503	Reporting of high-risk plaque was associated with more frequent ICA in CAD-RADS 1–2, stress testing and revascularization in CAD-RADS 3, and revascularization in those with CAD-RADS 4–5
Maaniitty et al. [75]	Treatment strategies	1973	CAD phenotypes defined by anatomical and functional imaging may help guide lipid-lowering therapy
D'Ascenzo et al. [76]	PCI management	606	CCTA follow-up after left main PCI was associated with less spontaneous myocardial infarction and more imaging-driven revascularization

AI-QCT, AI-guided quantitative CCTA; CAD, coronary artery disease; CAD-RADS, Coronary Artery Disease Reporting and Data System; CCTA, coronary computed tomography angiography; PCI, percutaneous coronary intervention.

step in the transition of CCTA from stenosis assessment to plaque-guided personalized therapy. Recent applications of CCTA in clinical decision-making are presented in Table 3 [71,72,73,74,75,76]. By enabling comprehensive plaque characterization, CCTA provides a valuable surrogate endpoint in therapeutic trials, supports personalized treatment strategies, and contributes to the optimization of PCI management.

6.1 Treatment Response Surveillance

CCTA-based plaque quantification provides important surrogate endpoints for treatment response assessment. By characterizing coronary plaque using CCTA, multiple studies evaluated the effects of lipid-lowering and anti-inflammatory therapies on plaque progression and regression, thereby enabling the noninvasive monitoring of treatment response [71,72,77,78]. Weichsel et al. [71] showed that moderate- or high-intensity lipid-lowering therapy considerably slowed the progression of total and noncalcified plaque, as assessed by CCTA. These studies indicate that CCTA can serve as an imaging endpoint for evaluating therapeutic efficacy in CAD, providing a valuable platform for drug development and clinical translation.

6.2 Impact of PCD-CT and AI on Treatment Strategies

PCD-CT substantially facilitates plaque characterization and may help identify patients truly requiring interventional treatment and thereby avoid unnecessary invasive procedures. Compared with EID-CT, PCD-CT was associated with fewer downstream referrals for invasive coronary angiography (9.9% vs. 13.1%); among patients who underwent ICA, a higher proportion received revascularization in the PCD-CT group (43.4% vs. 35.5%) [79]. AI-QCT improves diagnostic accuracy and can directly influence clinical management. In the multicenter CERTAIN study, 750 patients were evaluated with and without access to AI-QCT results [73], and physicians established diagnoses and planned noninvasive testing, revascularization, and medical therapy. The inclusion of AI-QCT data increased diagnostic confidence two- to five-fold, led to changes in diagnosis or management in nearly 60% of patients, reduced downstream testing in 37% of cases, and increased the use of preventive therapies. These findings suggest that CCTA-based plaque quantification can directly optimize clinical decision-making. However, three-month follow-up data from CERTAIN revealed a substantial gap between AI-QCT-guided recommendations and real-world implementation, underscoring the need for further efforts to translate imaging findings into clinical practice [80].

6.3 Impact of Plaque Characterization on Treatment Strategies

The CCTA-based identification of high-risk plaque has important implications for treatment strategies in patients with suspected CAD. In a large retrospective study of 21,503 patients, high-risk plaque reporting was associated with the increased use of invasive coronary angiography, stress testing, and revascularization across stenosis categories, although reporting remained infrequent and variable [74]. This low overall reporting rate and substantial interreader variability highlight the need for standardized training and supportive detection tools. Beyond plaque features, CAD phenotypes defined by anatomical and functional imaging were also linked to treatment patterns, with lipid-lowering therapy use increasing with disease severity in a stepwise manner [75]. In emergency settings, CCTA can be used for triage in patients with suspected acute coronary syndrome [69]. In low-risk patients, the high negative predictive value of CCTA allows safe discharge when its findings are negative. In intermediate-risk patients, CCTA may reduce the need for ICA and support more individu-

alized treatment management. These findings suggest that CCTA-based plaque characterization is closely associated with treatment selection and may enable more precise and individualized management.

6.4 PCI Management

Growing evidence suggests that CCTA can inform coronary revascularization planning, with AI facilitating the selection of optimal angiographic projections, delineation of plaque location and characteristics, optimization of PCI device selection, and refinement of revascularization strategies [81]. The ongoing PRECISION-CT study aims to evaluate the value of CCTA-guided PCI planning in real-world clinical practice [82]. Furthermore, the PULSE study showed that CCTA follow-up after left main PCI is associated with reduced spontaneous myocardial infarction and increased imaging-driven revascularization [76]. These findings suggest that CCTA may play an important role across the PCI pathway, from preprocedural planning to postprocedural follow-up, although further studies are needed to define its role in more complex subgroups.

7. Challenges and Opportunities

Although CCTA has enabled substantial progress in coronary plaque assessment, several key challenges must be addressed before its technical advantages can be translated into broad clinical benefit.

PCD-CT enhances spatial resolution and improves the accuracy of plaque assessment. However, its high cost and variability in reconstruction parameters lead to considerable differences in plaque composition quantification, and the absence of standardized protocols limits multicenter data comparability and broader clinical use [83]. LLMs can extract CAD-RADS 2.0–based structured information from CCTA reports, but their limited generalizability, along with data privacy and regulatory constraints, restricts clinical applicability. AI-based plaque analysis platforms can improve the efficiency of plaque quantification; however, the substantial variability across vendors, software platforms, and imaging protocols underscores the need for standardized analytical frameworks. Furthermore, many algorithms are developed and validated in selected cohorts, which raises concerns regarding dataset bias and performance in more diverse real-world populations. The limited interpretability of deep learning models also hinders clinical acceptance, particularly when algorithm outputs influence diagnostic or therapeutic decisions. Although many AI tools have demonstrated promising performance, their impact on routine clinical workflows requires further validation in prospective multicenter studies. In addition, the performance of CT-FFR is highly dependent on source image quality, and its broader adoption is limited by offline processing requirements, cost, and policy-related barriers [84].

Although technological advances have enhanced the prognostic value of CCTA-based plaque characterization beyond traditional risk factors, the corresponding clinical implementation is challenging. Several randomized controlled trials have supported the use of CCTA as a surrogate endpoint for treatment response; however, its wider adoption remains constrained by cost and radiation exposure. The translation of imaging findings into clinical action is often hampered by therapeutic inertia, and AI-generated treatment recommendations are not consistently implemented in real-world practice. Finally, management strategies for patients with nonobstructive stenosis remain inadequately standardized, and the comprehensive plaque characterization enabled by CCTA may help guide more refined clinical decision-making.

8. Conclusions

Advances in CCTA have markedly improved the assessment of plaque morphology, composition, and functional abnormalities. CCTA-derived plaque characterization provides independent prognostic value and supports individualized treatment decisions. Despite the remaining challenges in technical standardization, AI algorithm generalizability, and cost-effectiveness, CCTA has evolved into an important platform linking imaging findings to clinical decision-making.

Author Contributions

YG, WK, LL, AQJ, HX, and QC conceptualized and designed the research study. YG, WK, LL, and YLF were responsible for data analysis and drafting of the manuscript. YG, TZ, XYZ, JYL, GHX, CXS, and QC were involved in both the data interpretation and the review of the manuscript. HX and QC were responsible for funding acquisition. All authors contributed to editorial changes in the manuscript. All authors read and approved the final manuscript. All authors have participated sufficiently in the work and agreed to be accountable for all aspects of the work.

Ethics Approval and Consent to Participate

Not applicable.

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Conflicts of Interest

The authors declare no conflicts of interest.

Supplementary Material

Supplementary material associated with this article can be found, in the online version, at https://doi.org/10.31083/RCM53475.

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